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METHODS FOR MAPPING LAND COVER CHANGE IN SHRINKING CITIES IN THE UNITED STATES

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For my dad, Joe Thompson. Thank you for showing me how to be a fighter, to never lose faith, and to keep my eyes on the light at the end of the tunnel. You are my hero. I love you.

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Abstract

Urbanization is generally understood as the process of growth in both population and developed areas. However, this perception is not entirely reflective of the types of change that are occurring in the heart of the United States. The Rust Belt region of the United States was once the beacon of industrial power, but today is riddled with shrinking cities that have experienced a dark modern history laced with loss of industrial economies, drastic declines in population, and crippled governments. Residential and commercial properties in these cities have been prone to high rates of abandonment, decay, and demolition. While much of the research surrounding these shrinking cities focuses on socio-economic effects, few studies have investigated the physical artifacts of drastic population loss in the United States. This research aims to contribute to the growing body of shrinkage research by examining two cost-efficient methods of monitoring the fast removal of buildings in the Rust Belt shrinking cities of Detroit, Michigan and Youngstown, Ohio. This goal is achieved through the use of a range of different data sources: Light Detection and Ranging, aerial orthoimagery, and GIS datasets all of which are publicly available. We map a 5-year change in Detroit as well as a 10-year and 19-year change in Youngstown to provide, in high detail, an example of how publicly available geospatial data can be applied to identify change in the urban landscapes of the American Rust Belt. The methods used are reproducible and ideal for municipalities that are aiming to monitor building removal in a cost-efficient manner.

Chapter 1: Introduction to Shrinking Cities and Housing Abandonment in the United States

Approximately 80% of the population of the United States resides in an urban area. With the global urban population projected to exceed 6 billion people by 2050, that proportion is expected to near 90% (DESA, 2014). Although more people are beginning to reside in urban areas, the spatial distribution of urban population growth in the United States is not uniform. Continuous population growth is expected to occur in the dominant cities of New York City, New York; Chicago, Illinois; and in cities along the western coast centered on Los Angeles, California. The Texas metropolises of Dallas, Fort Worth, Houston, Austin, and San Antonio as well as the Phoenix, Arizona metropolitan area are considered to be some of the fastest growing cities in the United States (United States Census Bureau, 2016).

While cities experiencing the strongest growth in populations are predominantly scattered along the coastal and southern regions of the country, several cities in other areas have been declining in population for several decades. For these cities in decline, some have experienced population declines in excess of 50% (Robert A. Beauregard, 2009).

The standard term for a city that has experienced drastic and sustained population decline is a “shrinking city” (Hollander, 2010). Urban shrinkage is not isolated to the United States and a fair amount of research has focused on the rebuilding and restructuring of shrinking cities in post-World War II eastern European countries. In the United States, cities located in the “Rust Belt” region of the U.S. serve as the classic examples of shrinking cities. This colloquially-defined region of the country spans from western New York state and Pennsylvania across the Midwestern states of Ohio, Michigan, and Indiana into portions of northern Illinois and far southern Wisconsin. The Rust Belt is home to cities such as: Detroit, Michigan, Buffalo, New York, Toledo and Cleveland, Ohio, Pittsburgh, Pennsylvania, and Indianapolis, Indiana which are all major industrial centers for automotive and mining industries. Smaller cities such as Youngstown, Ohio; Parkersburg, West Virginia; and Gary, Indiana help to make up the predominantly industrial, also referred to as “blue collar” workforce of this region. Prior to the 1930s, very few cities in the United States experienced shrinkage and those that did were because of relocation of port and railroad businesses (Robert A Beauregard, 2003). While the cities of Chicago and Indianapolis have continued to grow in population, most of the other cities within the Rust Belt have been declining significantly since their peak populations were reached, respectively (**Table 1**). The causes of shrinkage varies from city to city, but the most common cause in Rust Belt cities is economic struggle induced by the decline of mining operations, technological advancements that lured employees away from the city, and the decentralization and relocation of industrial corporations (Martinez-Fernandez, Audirac, Fol, & Cunningham-Sabot, 2012; Siljanoska, Korobar, & Stefanovska, 2012; Wiechmann & Pallagst, 2012).

Table 1: Population Changes from Peak-2010 in Rust Belt Cities

City	Peak Population (*Year*)	Population 2010	% Change
Detroit, Michigan	1,849,568 (*1950*)	713,777	-61%
Youngstown, Ohio	170,002 (*1930*)	66,982	-61%
Cleveland, Ohio	914,808 (*1950*)	396,815	-57%
Pittsburgh, Pennsylvania	676,806 (*1950*)	305,704	-55%
Buffalo, New Yok	580,132 (*1950*)	261,310	-55%
Gary, Indiana	178,320 (*1960*)	80, 294	-55%
Toledo, Ohio	383,818 (*1970*)	287,208	-31%
Parkersburg, West Virginia	44,797 (*1960*)	31,492	-30%

Detroit, Michigan has long served as the poster-child for urban shrinkage. Following a rapid population increase as a result of the military buildup associated with World War II, racial tension began to flare in the predominantly white city. The Race Riots of 1943 served as the crux for population decline. Post-WWII Detroit saw the beginnings of the “white flight” out of the city center into suburbia (Jego, 2006; Sugrue, 2014; Thomas & Bekkering, 2015; Thompson, 2004). With this flight came economic downturn when several large automotive plants, such as the Packard Plant, were forced to declare bankruptcy and eventually close. Population loss and economic decline were perpetuated following the second round of race riots in 1967 in which thousands of businesses were vandalized or destroyed, causing upwards of $50 million in damages to the city. The 1967 riots continued to push financially stable families from the city into a safer suburbia and resulted in low income peoples moving into the city center (Jego, 2006; Sugrue, 2014; Thomas & Bekkering, 2015; Thompson, 2004). Unable to produce enough tax revenue to revitalize businesses that were lost in the riots, Detroit’s economy continued to flounder with increasing numbers of job and urban population losses.

Once known as the gem of “Steel Valley,” the city of Youngstown has continued to lose population since its peak in 1930. During the 1930s and 1940s, the decline in population occurred at a slow rate, but following a strike of steel mill workers during the height of the Korean War in the early 1950s, the rate of decline increased rapidly. Youngstown’s economy crumbled following the seizure of the city’s steel mills at the hands of the federal government during the strike. In addition to difficult employment conditions, extreme segregation in the city provoked the destruction of black neighborhoods in exchange for ghettos. Much like Detroit, the turbulent environment led to race riots in the early 1960s and assisted in people leaving the city. During this period, organized crime seized control of many facets of the government up through the 1990s, encouraging and increase in violent crime rates for which the city is still notorious.

The consistently declining populations in addition to the lack of economic opportunity have led to an increase in the number of vacant and abandoned properties in shrinking cities, most notably in Detroit and Youngstown. Although the struggles with land abandonment have been plaguing the rust belt for decades, the number of vacant and abandoned homes increased significantly in shrinking cities following the 2008 housing crisis which struck the United States which caused hundreds of thousands of home foreclosures following (Martinez-Fernandez et al., 2012; Ryan, 2008). While some of the literature uses the terms “vacant” and “abandoned” interchangeably, here the definitions outlined in (Hillier, Culhane, Smith, & Tomlin, 2003) are adopted; where vacancy is identified as a temporary state and abandoned indicates a permanent state. Vacancy most commonly refers to vacant lots in which a building once stood, but has been removed and where development projects could potentially occur. Physical abandonment of a home occurs when no persons have resided in the property for at least two years (Hollander, Pallagst, Schwarz, & Popper, 2009) and the property itself has been neglected (i.e. overgrown vegetation, broken windows, missing roof shingles, etc.). Financial abandonment occurs when a person has discontinued their financial responsibility (most commonly a mortgage loan). In most cases, financial abandonment leads to physical abandonment (Hillier et al., 2003). Unattractive homes become difficult to sell which then leads to a continued lack of physical maintenance and ultimately puts a building on the path to becoming structurally compromised, eventually disintegrating into shambles and posing a threat to neighborhood residents (Alsup, 2016). As a result, recent literature has begun to call for research on the changing land cover patterns that are emerging in shrinking cities (Frazier, Bagchi-Sen, & Knight, 2013; Großmann, Bontje, Haase, & Mykhnenko, 2013; D. Haase, 2013).

Most cities have an independent form of managing changes in development, but the most common approach that still exists in shrinking cities is a pro-growth strategy which encourages the sale of land to be used in development. Criticisms of pro-growth strategies show that its roots lie in trickle-down economics which has often been accused of favoring the wealthy, however such an approach could help jumpstart the struggling economies of shrinking cities (Weaver, Bagchi-Sen, Knight, & Frazier, 2017). Detroit has made strides to promote the revitalization of their downtown region through large scale development projects such as the building of the Cabo Center, which cost roughly 280 million dollars, in an effort to encourage private investments in developments.

Detroit uses a pro-growth strategy that manages vacant lots and abandoned properties through two main approaches. The first focuses on the cheap sale at of properties at auctions, however these auctions often do not occur in the most distressed areas of the city. Dewar and Thomas (2012) found that from 2002-2010, only 18% of the properties from neighborhoods with high rates of vacant and abandoned properties available at auction were purchased and an overwhelming majority of those were sold to real estate companies in hopes that it would increase the amount of urban development. The second pro-growth strategy used in Detroit is one of demolition - intentionally clearing vacant and abandoned properties owned by the city to be used for private development. While both strategies aim to achieve economic growth by encouraging redevelopment, the demolition course has been heavily favored over auction based sales of land (Dewar & Thomas, 2012; Weaver et al., 2017). Additionally, neither of these methods have alleviated the declining population. The United States Census Bureau (2015) estimates suggest that the population is still declining, reaching its lowest population since the early 1900s.

Although several shrinking cities have adopted pro-growth strategies, Youngstown, has blazed the trail toward a management strategy that aims to provide a sustainable future for the residents of their city rather than the encourage the growth of new populations. This approach, known as “smart-decline” (Hollander et al., 2009; Rhodes & Russo, 2013), allows urban planners to plan for fewer people, making their job focus more on sustainable small scale development rather attempting to plan large scale development that may never come. Similar to pro-growth strategies, smart-decline has a strong focus on demolition of abandoned properties and favors vacant lands for alternative uses such as community gardens and parks in lieu of heavy redevelopment (Schilling & Logan, 2008).

Many of America's Rust Belt cities have been consistently declining in population for over 50 years primarily as a result of the decentralization and relocation of industrial jobs, racial tensions, and increase crime rates within the city. Combined, these issues have led to an increase in the number of vacant and abandoned properties which have been left to rot. The presence of these properties makes it challenging for cities to encourage investment from private industry and convince new people to move into their city (Hackworth, 2015; Hackworth & Nowakowski, 2015; Rhodes & Russo, 2013). Multiple management styles exist for handling these abandoned lands. Two notable approaches are that of pro-growth that is used in Detroit and smart-decline which is used in Youngstown. While both aim to assist their respective economy and influence declining populations in different ways, they are common in that they both include strong demolition efforts to fight blight in their cities. These programs have encouraged the rapid removal of buildings over the course of the last decade and have increased the number of vacant lots. The fast paced demolition of structures could potentially have environmental impacts (A. Haase, Rink, Grossmann, Bernt, & Mykhnenko, 2014; D. Haase & Schetke, 2010) that have yet to be explored in shrinking cities, thus monitoring where building removal is occurring is important to the body of shrinkage literature. This research aims to explore methods for which building removal can be monitored in a cost effective manner and attempts to provide city-wide maps of changes in urban land cover of two Rust Belt shrinking cities.

Chapter 2: Tracking the Removal of Buildings in Rust Belt Cities with Open-Source and Public Geospatial Data

2.1. Introduction

Exploring changes in urban land cover is important for understanding how human-environmental interactions impact natural processes and biodiversity in a region. In addition to removing native plant and animal species, the introduction of built environment can alter air quality and have damaging downstream effects on water quality and quantity (Foley et al., 2005; Grimm et al., 2008; Kowarik, 2011; McKinney, 2008). Because the global urban population is projected to increase to nearly 5 billion people by 2030, undoubtedly placing significant stress on already strained resources (Seto, Güneralp, & Hutyra, 2012), many urban land cover change studies tend to focus on rapidly urbanizing regions (Bhatta, Saraswati, & Bandyopadhyay, 2010; Hegazy & Kaloop, 2015; Jat, Garg, & Khare, 2008; Xu & Min, 2013). However, over the course of the last half-century, a dichotomy of urban environments has emerged in multiple regions of the world (A. Haase et al., 2014), but most notably in the United States. While the U.S. is home to several rapidly expanding metropolises, once-prosperous industrial centers are overshadowed and have steadily lost population.

A city experiencing significant population decline in addition to decline in economic prosperity is known as a “shrinking city” (Robert A. Beauregard, 2009; Pallagst et al., 2009). The research surrounding the causes of shrinkage is vast, with many studies noting that the decentralization of industry, demographic tensions, crime, political corruption, and the shift in industrial power have contributed to the shrinkage problem across several areas of the globe (Rieniets, 2009; Ringel, 2014; Schetke &

Haase, 2008; Weaver & Holtkamp, 2015; Wiechmann & Pallagst, 2012). The majority of the most significantly shrinking cities in the U.S. are isolated to the Rust Belt region. This colloquial region spans roughly 500 miles across the heart of the U.S. and represents the spatial extent of the early twentieth century's economic backbone. Much of the shrinkage research focusing on the U.S. examines cities such as Pittsburgh, Pennsylvania; Cleveland, Ohio; Detroit, Michigan; and Buffalo, New York which are all located within the Rust Belt (Rosenthal, 2008; Schilling & Logan, 2008; Weaver et al., 2017; Zingale & Riemann, 2013).

Almost exclusively, the body of U.S. shrinkage research discusses the aforementioned contributors to population decline, but there has been a push toward examining the shifts in land use as a result of population loss (Hollander et al., 2009; Pallagst, 2010). Thomas and Bekkering (2015) used historical maps to show the progression of urbanization in Detroit. Additionally, they mapped historical land use in the city, but this does not provide much information on the actual presence of buildings. They did examine the presence of buildings on parcels of land in some portions of the city, but this was limited due to the datasets being used. Hollander (2010) conducted a case study of three neighborhoods in Flint, MI in which in-situ photographs were compared to population dynamics to examine reflections of population shifts on housing density. While this study was effective for the small study areas, the approach would not be ideal for an entire city. Hillier et al. (2003) used a large information system to monitor risk of housing abandonment in Philadelphia, PA. This study is notable in that it not only makes use of a large database, but it also identifies indicators of physical abandonment of a property such as overgrown vegetation. Most cities have property information systems available through tax assessors, but they do not often contain property characteristics other than basic ownership, lot size, and address information. Replication of this study in a region with limited resources would require a significant amount of ancillary data. Ryznar and Wagner (2001) used remote sensing data (Landsat) to map urban greenness in Detroit, Michigan as a proxy for shifts in demography. This study found increased greenness in areas of suspected abandonment in addition to moderate to higher income areas. Although this study provides a snapshot of how the removal of the human influence from a property can change its land cover and biodiversity, it provides no information about the impacts of abandonment on the built environment.

Urban shrinkage is not limited to the USA only. For example, D. Haase, Seppelt, and Haase (2008) examine land use changes in Leipzig, Germany as a result of shrinkage while suggesting that demolition of the built environment could influence fragmentation and ecological restoration. This suggests that examining the changes in the built environment is key to understanding how population loss not only influences the landscape, but also how that relationship provides positive feedback to natural processes that take place in these regions. Additionally, examining changes in built environment over time could assist in smart and sustainable shrinkage that will maximize environmental benefits (Rhodes & Russo, 2013).

The manner in which land cover change studies are conducted in urban areas varies based on the nature of the environment being explored, but some of the most effective ways to analyze changes in urban land cover characteristics are through the use of remotely sensed and GIS datasets which allow the landscapes to be displayed in high detail (Xiao et al., 2006; Yang, Xian, Klaver, & Deal, 2003; Yuan, Sawaya, Loeffelholz, & Bauer, 2005). Many studies use remotely sensed products such as Landsat data with a moderate resolution of 30-meters to examine urban land cover for multiple years (Fu & Weng, 2016; Sexton et al., 2013; Song, Sexton, Huang, Channan, & Townshend, 2016; Stefanov, Ramsey, & Christensen, 2001). While this publicly available product has been proven to be effective at analyzing large scale changes across urbanizing areas, the moderate resolution proves to be too coarse to use in shrinking cities research due to the overgeneralization of the landscape which misses small details on the surface (e.g. the removal of a small, singular structure such as a residential home).

Classified products such as the National Land Cover Database (NLCD), a Landsat-derived product generated by the U.S. Geological Survey which contains 16 land cover classes and has a 30-meter resolution (Homer et al., 2015), have appeared in the literature throughout the last decade and showcases density of the built environment with four different classes (Milesi, Elvidge, Nemani, & Running, 2003; Mitsova, Shuster, & Wang, 2011). As mentioned previously, spatial resolution is a problem, but even more so is the NLCD's inability to revert a pixel in its urban density (Jin et al., 2013), that is, once a pixel is classified as a certain urban density, it will either remain unchanged or increase in density from year to year. Thus, using the NLCD to examine changes in the built environment in a shrinking city would yield inaccurate results.

Technological advances over the years have allowed for high and very high resolution products such as WorldView, Quickbird, and Ikonos to be used to analyze change in great detail, however, these products are often not freely available and can become quite costly when the aim of a study is to explore the landscape of an entire city (Herold, Couclelis, & Clarke, 2005; Myint, Gober, Brazel, Grossman-Clarke, & Weng, 2011; Novack, Esch, Kux, & Stilla, 2011; Pu, Landry, & Yu, 2011; Zhou, Huang, Troy, & Cadenasso, 2009). Using products such as these would yield results in high detail, but would be not be an ideal expenditure for cities that are struggling financially. Orthophotos are a viable alternative (Taylor & Lovell, 2012). Ortho imagery is often publicly available for multiple years and are usually flown at very high resolutions such as 1-foot or 0.5-foot resolutions, making features on the landscape easy to visually identify.

An additional alternative is to use Light Detection and Ranging (LiDAR) data which is also publicly available and has the ability to showcase small details on the landscape at a very high resolution. LiDAR data provides the opportunity for complex landscapes to be identified while avoiding classification limitations associated with mixed spectral signatures. Much of the literature surrounding LiDAR research with respect to urban environments focuses on building detection and feature extraction (O'Neil-Dunne, MacFaden, Royar, & Pelletier, 2013; Verma, Kumar, & Hsu, 2006). Features can be extracted from the LiDAR point cloud (Tarsha-Kurdi, Landes, Grussenmeyer, & Koehl, 2007), from a digital surface model derived from the point cloud (Priestnall, Jaafar, & Duncan, 2000), or by using a combination of LiDAR data and other products such as aerial imagery, high resolution satellite imagery, and GIS databases (Cheng, Gong, Li, & Liu, 2011; Singh, Vogler, Shoemaker, & Meentemeyer, 2012; Sohn & Dowman, 2007; Wu, Sun, Yang, & Yu, 2016). Building feature extraction has been shown to be an effective means of analyzing the landscape, but we have not found any literature that explores the use of building feature extraction from LiDAR data to analyze shrinking cities.

Here, we use publicly available LiDAR data, orthophotos, and GIS databases to identify the removal of structures in two U.S. shrinking cities and explore the rates at which shrinking cities are removing structures through demolition. In our first case study, we use extracted building footprints from LiDAR in combination with GIS survey data to classify changes in parcels. In our second case study, we use aerial imagery and demolition records to identify changes in parcels. As mentioned previously, while there are examples of some studies that have examined land use change in shrinking cities, we have not been able to find a city-wide analysis of how the presence of structures is shifting in the literature. We aim to map changes at various time scales and providing a snapshot of the contemporary urban landscape in the Rust Belt region of the United States.

2.2 Study Region

The Rust Belt of the United States stretches from western New York state to far east Illinois and includes areas of western Pennsylvania as well as the states of Ohio, Michigan, and Indiana. The cities within this region were once primarily populated by the workers of the automobile and steel manufacturing industries, but many of them have been losing their populations since the height of the twentieth century. **Figure 1** shows the span of the Rest Belt for reference in this study. Because this region does not have a formal administrative boundary we created this figure by selecting cities that were identified as being typical Rust Belt manufacturing locations in Hobor (2013). A 20 mile (32.2 km) buffer was created around each city to represent the mean U.S.

commuter distance to work which was identified in Rapino and Fields (2013). We then used the outermost portions of the buffers to create a boundary which encompasses all of the cities selected. Although the Rust Belt was once the standard for success in the industrial age, it is now characterized by its financial hardship and steady population decline. Notably contained within the region are the cities of Detroit, Michigan and Youngstown, Ohio which have been selected for analysis in this study.

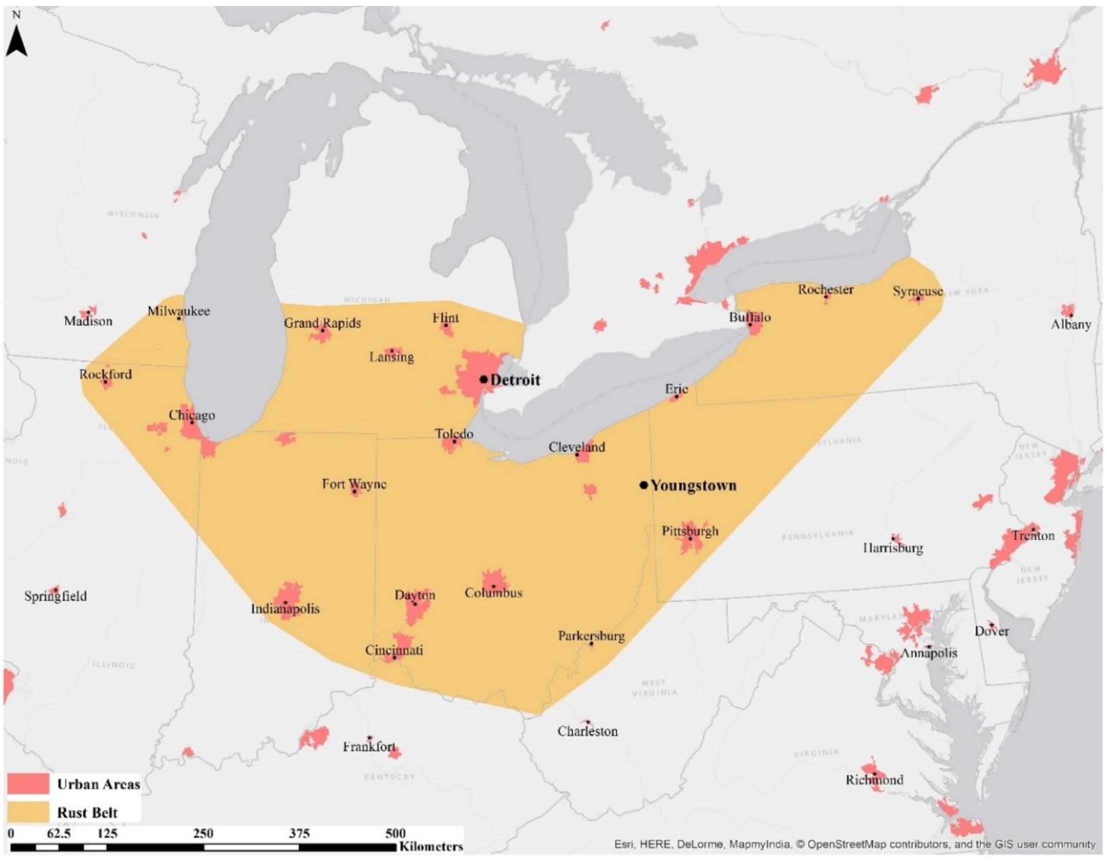

Figure 1: Rust Belt Region of the United States. The Rust Belt Region of the United States spans hundreds of kilometers and includes industrial centers of the metals and automotive industries. Basemap and Urban Areas © ESRI.

Detroit often serves as the prime example for shrinkage (Wiechmann & Pallagst, 2012) because of its early rise to prominence in the automobile industry followed by its decades long spiral into socio-economic hardship. Detroit has an estimated current population of less than 690,000, but it has been grappling with drastic population loss since the height of the twentieth century. The city reached its peak population of 1.85 million in 1950 and suffered a 61% decline to 711,000 by 2010 (United States Census Bureau). The significant shrinkage came as a result of the decentralization and dispersion of the automobile industry, increased crime rates, political corruption, and economic downturn (Martinez-Fernandez et al., 2012; Siljanoska et al., 2012). Although Detroit continues to lose population, it has made significant strides to monitor the impacts of population decline on the landscape.

Similar to expansive Detroit, Youngstown (estimated population of 65,000) has grappled with socio-economic challenges, but on a much smaller scale. Youngstown reached its peak population of 170,000 in 1930. By 2010, the population of the steel town had fallen by 60% to 67,000 (United States Census Bureau, 2010). Also like Detroit, Youngstown has made significant efforts to fight blight by adopting a smart shrinkage plan which emphasizes the removal of abandoned structures in an effort to make the city more sustainable (Rhodes & Russo, 2013).

Detroit and Youngstown were selected for this study in an effort to provide a dichotomy of sizes – showing that not just large cities are impacted by the shrinkage problem. Additionally, the differences in data availability for each city made for interesting comparison and the need for different methods of analysis.

Detroit is contained within Wayne County in southeast Michigan and is nested along the Detroit River, which flows into Lake St. Clair to the Northeast and Lake Erie to the Southeast. For this study, we use the official municipal boundary of the City of Detroit, which expands 370 km^2 (**Figure 2a.**), while neglecting the centralized communities of Hamtrack and Highland Park as well as all communities surrounding the city.

Youngstown is contained primarily in Mahoning County is eastern Ohio, but a small fraction of the city expands into Trumbull County. Again, we will use the official municipal boundary for the City of Youngstown. This boundary has an area of 90 km^2 (**Figure 2b.**)

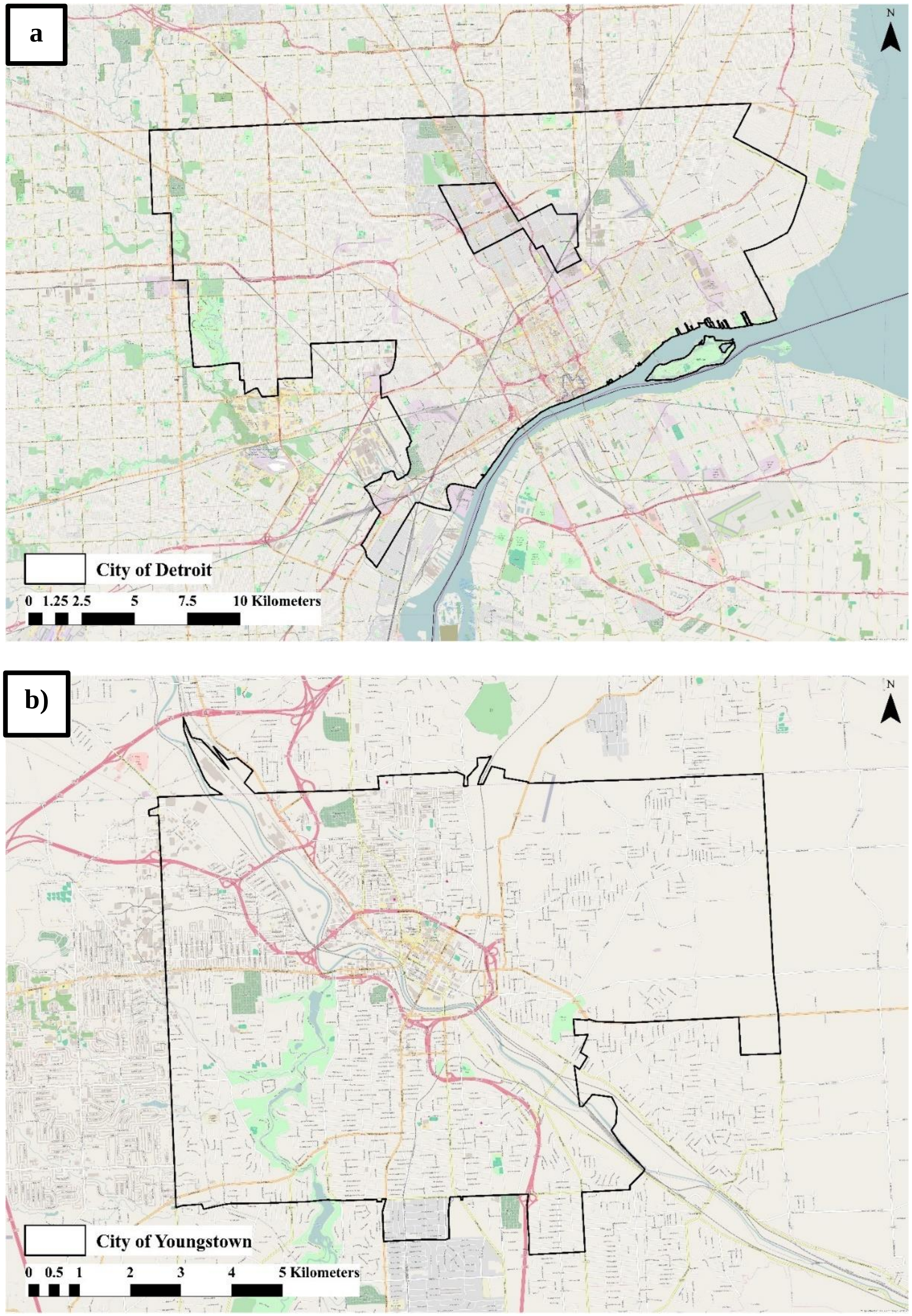

Figure 2: a) Municipal boundary of Detroit, Michigan. b) Municipal boundary of Youngstown Ohio. Basemap source: © OpenStreetMap contributors, CC-BY-SA.

2.3. Data

2.3.1 Parcel Data

We used administrative parcel data that is survey grade in both Detroit and Youngstown. Residential parcels are approximately half the width of a 30-meter resolution pixel and allowed for a higher resolution classification that considered small details, i.e. residential structures, on the surface. Parcel data for Detroit was retrieved from the Data Driven Detroit (D3) web portal (http://datadrivendetroit.org/). Parcel data for Youngstown was retrieved from the Youngstown State University GIS Mapping and Data Center (http://cms.ysu.edu/administrative-offices/redi/gis-mapping-and-data-center).

2.3.2 LiDAR Data

Airborne Light Detection and Ranging (LiDAR) data is a remote sensing product generated by using pulses of laser (LAS) light to sample the Earth's surface and provide three dimensional point data of the terrain (Liu, 2008). Typically collected via aircraft, LiDAR gathers z coordinate (elevation above the surface) point data by transmitting pulses of light on an x,y (latitudinal, longitudinal) grid and recording the time elapsed from transmission to reception by the receiver (Zhang et al., 2003).

LiDAR points can have many returns of the light pulses, but the first return measures the highest point the light contacts. The first return points often represent the rooftop of a building, top of vegetation canopy, or ground (if vegetation such as trees are not present). Because they are solid features, buildings often only have one return that represents the rooftop due to the inability of light to penetrate beyond that point (Zhang, Yan, & Chen, 2006). A point may have multiple returns if it has a complex structure of multiple elevations. For example, LiDAR data can be used to identify trees because they often have many returns due to their complex spatial structure (Guo, Chehata, Mallet, & Boukir, 2011).

We retrieved 205 2.25 km^2 LiDAR scenes, **Figure 3**, from the USGS Earth Explorer website (http://earthexplorer.usgs.gov/) for Detroit from the 2009 USGS Wayne County LiDAR dataset. This scene shows a typical LiDAR point cloud classified by elevation (meters). The LiDAR for this project was flown from 16 April 2009 through 3 May 2009. This topographic LiDAR dataset was collected as part of the 3D Elevation Program under the USGS' The National Map initiative. Following collection, points were classified to LAS version format specifications outlined by the American Society for Photogrammetry and Remote Sensing (ASPRS). The number of classes has grown considerably in recent years with updates to LAS format versions. Classes in current ASPRS format versions are extensive and include highly detailed information such as power lines. Previous formats were more limited in classification classes. **Table 2** outlines classes included in ASPRS LAS version1.1. The raw LIDAR point clouds for Detroit were downloaded in ASPRS LAS format version 1.1 and included the following classes: 1-Unclassified, 2-Ground, 7-Low Point (noise), 8-Model key-point (mass point), and 12-Overlap Points. According to ASPRS (2005), points classified as 1-Unclassified could be classified as structures, but were not explicitly assigned as such by the building classification algorithm that is used. This data was collected at a minimum resolution of one point per square meter and has a vertical accuracy RMSE of 18 cm.

Table 2: LIDAR classification descriptions adapted from (ASPRS, 2005)

Classification	Description
0	Never Classified
1	Unclassified*
2	Ground
3	Low Vegetation
4	Medium Vegetation
5	High Vegetation
6	Building
9	Water

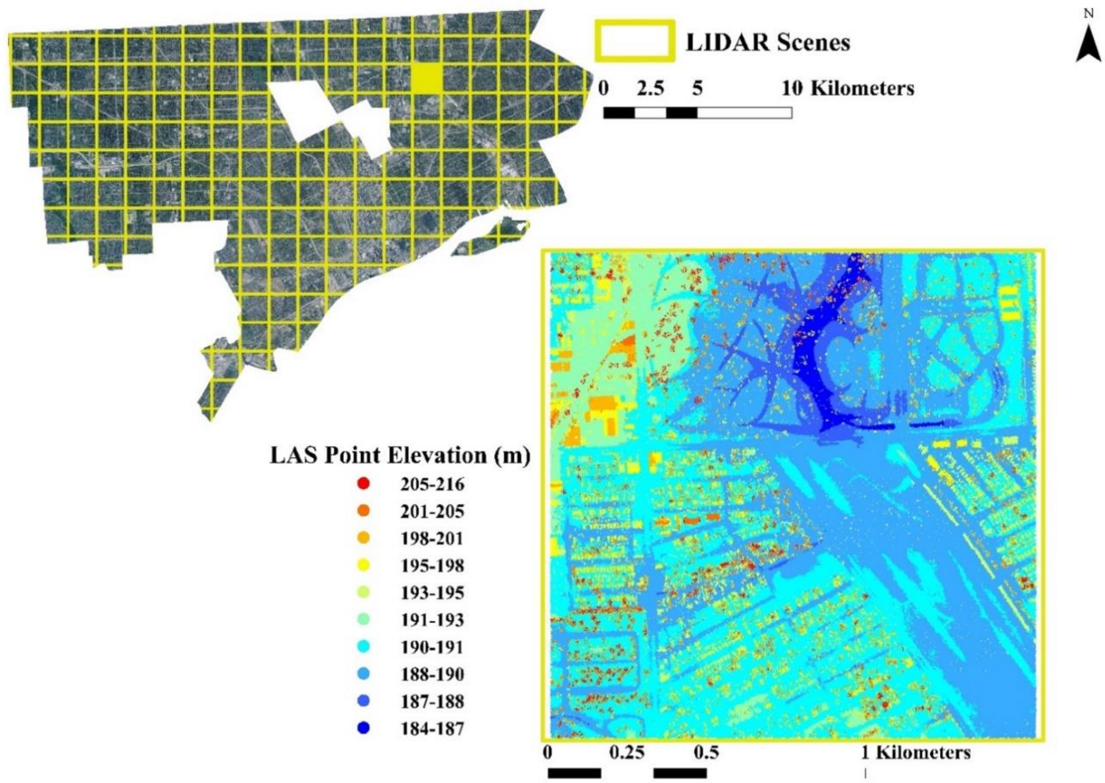

Figure 3: LIDAR scenes that were used for building detection in Detroit, MI. The shaded box denoted in on the city map (left) represents the geographic location of the inset sample LIDAR scene (right). Inset shows the point cloud classified by elevation for one 1.5 km^2 scene.

2.3.3 Orthoimagery in Youngstown

Orthophotography for 1998, 2006, and 2013 was used in lieu of LiDAR data for the City of Youngstown. Orthophotos are aerial photographs that have been digitally corrected to account for feature displacement (USGS) (https://lta.cr.usgs.gov/high_res_ortho). These images were collected as part of the Ohio Statewide Imagery Program (OSIP). The 1998 and 2006 images have resolutions of 1 foot while the most recent 2013 product has a resolution of 0.5 feet. Data was accessed through the Ohio Geographically Reference Information Program (OGRIP) web portal (http://ogrip.oit.ohio.gov/).

The 2006 orthophotos were flown by the State of Ohio in the months of March and April in leaf-off conditions. The 2013 orthophotos were flown by Mahoning County in partnership with the Ohio Statewide Imagery Program as part of the 2013 Mahoning County Digital Orthoimagery Project. Similarly to the 2006 dataset, the 2013 images were gathered in the spring during leaf-off conditions.

2.3.4 Survey Data in Detroit

2.3.4.1 2009 Detroit Residential Parcel Survey

The Detroit Residential Parcel Survey (DRPS) was one of largest surveys ever conducted in Detroit at the time of its collection in 2009. This survey explored residential properties that contained four or fewer units (i.e. it excluded large apartment complexes) in an effort to combat blight occurring within the city (http://www.detroitparcelsurvey.org). This data is gathered at the parcel level and is provided as a vector dataset. Information from this survey includes building type, condition, and vacancy. Additionally, this survey included a count of vacant lots. In total, the DRPS surveyed 90% of the parcels in the city, excluding large multi-unit residential properties and commercial properties. The DRPS was collected in August and September 2009. The data was accessed through the Data Driven Detroit (D3) web portal and, for this study, was used as a validation dataset for the LiDAR building detection method.

2.3.4.2 2014 Motor City Mapping Survey

In order to examine land cover change over a period of time, the Motor City Mapping Winter 2013-2014 Certified Results dataset was used in conjunction with the 2009 LIDAR data. This data was also accessed through the D3 web portal. The Motor City Mapping project, which will henceforth be referred to as MCM, was a collaborative effort amongst multiple Detroit and Michigan based organizations to provide detailed information for the 379,549 property parcels in Detroit. Initial data collection occurred from December 2013 through February 2014 and included data such as residency status, property type, structural status, structural condition, fire damage, etc. This survey was conducted in an effort to track and combat the property vacancy problem that has been plaguing the city for nearly six decades.

Although the survey includes extensive information, for the sake of this study we focused solely on the structure data that was provided. Simply, this information allowed us to identify if a structure (residential and commercial) was present on a parcel in the 2013-2014 timeframe. The MCM was performed approximately 5 years after the LiDAR data was collected for this area.

2.3.5 GIS Data in Youngstown

Demolition data was collected by the City of Youngstown Property Code Enforcement and Demolition Office and retrieved from the Youngstown State University Regional Property Information System (http://cms.ysu.edu/administrative-offices/redi/regional-property-information-system-rpis). The demolition dataset includes is presented as spatial point data beginning in 2006 and is updated frequently as new demolition projects are added. Currently, the dataset includes completed projects through spring of 2016.

2.4. Methods

The research methods for these case studies specifically focus on the presence or lack of buildings (i.e. we do not acknowledge vegetation). In both case studies, we classify parcels of land by determining if a structure was present on the land at specified time periods. In Detroit, we used LiDAR data to extract building features from the surface, which were then used to classify parcels of land, as well as data from the MCM survey. In Youngstown, we used orthophotographs and spatial demolition records to classify parcels. In both studies, the classified datasets were used to create change maps.

2.4.1 LiDAR Feature Extraction in Detroit

Building footprints for Detroit were extracted from the LiDAR dataset by using a point cloud based data-driven extraction method (Le, Kholdi, Xie, Dong, & Vega, 2016). Briefly, the LiDAR data points were divided according to their classifications, listed above. This division separates building points from bare-earth, vegetation, roadway, and other feature points. After the points are divided, non-building points are removed and points believed to be building points are isolated and grouped. Here, we focus specifically on above-ground groupings of point class 1-Unclassified due to a lack of a building class. As mentioned previously, in some LiDAR formats, the 1-Unclassified class is used in lieu of the 6-Buildilngs class. Using the grouped building points, line segmentation and smoothing techniques that will connect the boundary points of the building groups to create a building footprint polygon are applied (Cheng et al., 2011; Miliaresis & Kokkas, 2007; Sampath & Shan, 2007; Wang & Shan, 2009). The created building footprints are exported as a GIS shapefile. This methodology is made available in the ENVI LiDAR feature extraction workflow (Exelis Visual Information Solutions) and has been visualized in **Figure 4.1 and 4.2**.

2.4.2 Parcel Classification in Detroit

While independent usage of LiDAR extracted building footprints provides a snapshot of the urban landscape of Detroit in 2009, it suggests little in terms of how the built environment has changed since then. In order to provide a uniform base from which to explore changes in the built environment as well as provide a more recent visual of the urban landscape for the majority of Detroit, we chose to classify parcels for the years 2009 and 2014 using the building footprints extracted from LIDAR and the MCM survey respectively.

Parcels for 2009 were classified using a data layer intersection method. Here we overlaid footprint data on parcels and identified where present footprints intersected with a parcel. The parcels were classified using a "footprints" or "no footprints" code (**Figures 4.2 and 4.3)**.

Parcels for 2014 were classified by performing an attribute selection using the "Structure" field from the MCM. Here we classified the parcels with a "structure" or “no structure” code and removed parcels (for both 2009 and 2014) that were identified as “unknown.”

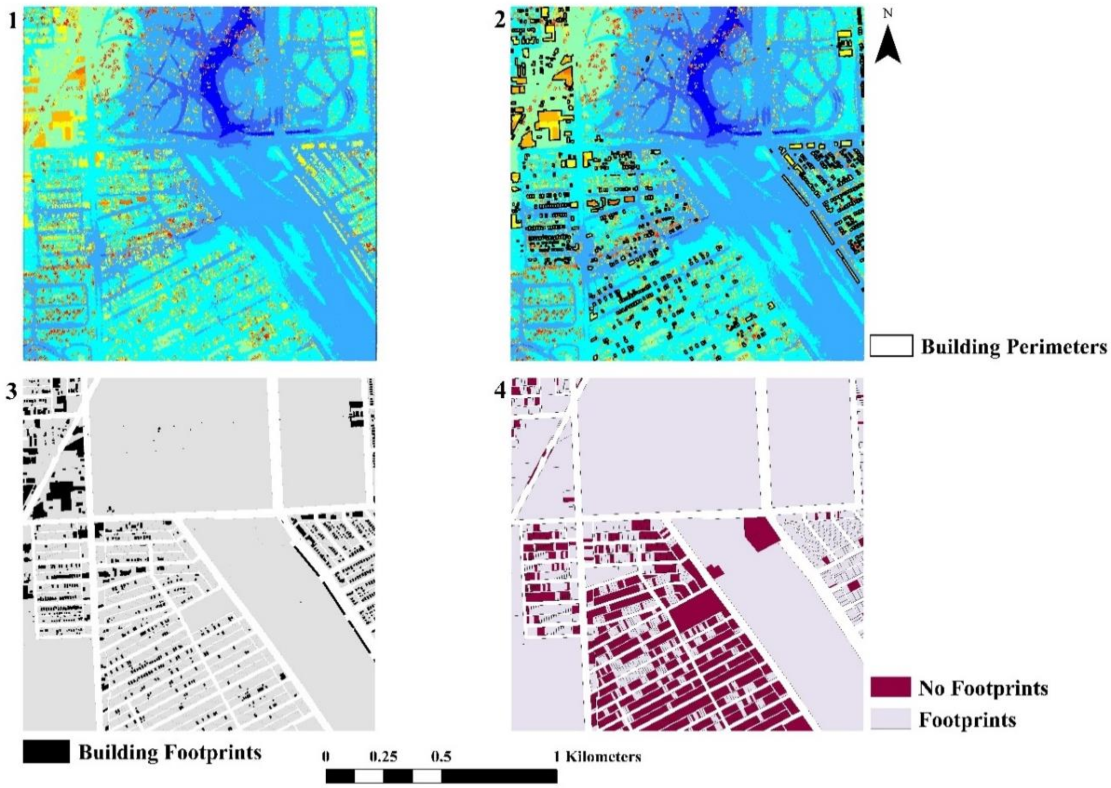

Figure 4: Workflow of feature extraction to parcel classification. 4.1. Raw LIDAR point cloud for a 1.5 km^2 scene (see Figure 3 for scene reference). 4.2. Building points are identified and perimeter contours are drawn. 4.3. Building footprints are extracted from the identified perimeter contours. Here the building footprints are overlaid on the matching property parcels. 4.4. Parcels are classified through intersection with the footprints as containing a building or not containing a building.

2.4.3 Orthophotography in Youngstown

Contrary to Detroit, Youngstown does not maintain a city-wide survey dataset with structure information and available LiDAR from 2006 had very low point density (~2/10m^2) which made the use of the previously specified feature extraction tool ineffective. Therefore, different data were required to examine changes to the built environment through time.

Instead, we manually classified parcels using orthoimagery for three non-consecutive years: 1994, 2006, and 2013. We again chose to use parcel level data to provide uniformity throughout the years and allow for a comparison with other cities such as Detroit. The parcel data used is from 2016, however the administrative parcel sizes and locations are not likely to change throughout time, especially in established cities such as Youngstown. Parcel data was overlaid onto imagery and structures were identified in the images. We used a binary classifier where 1 = structure present and 0 = no structure present to study 6,474 parcels in south central Youngstown.

2.4.4 Demolition Records in Youngstown

In addition to orthoimagery, parcels were classified using Youngstown demolition records. To combine the demolition point data with parcels, a spatial join was performed using ArcGIS software. We then identified the total number of parcels in which a demolition record was present and classified them using a "demolished structure" code.

2.5. Results

2.5.1 Feature Extraction Validation using the Detroit Residential Parcel Survey

The LiDAR feature extraction was validated using 339,983 parcels that were surveyed in the 2009 DRPS. Because the survey dataset was developed via in-situ data collection, we accept the DRPS as a ground truth dataset. As mentioned previously, this survey examined residential properties (excluding large apartment complexes and other types of private or commercial properties). This survey also accounted for vacant parcels.

We identified the number of parcels in which both the DRPS and the feature extraction tool identified a structure; the number of parcels in which the DRPS identified a structure and the feature extraction tool did not (and vice versa). We examined similar characteristics of vacant properties (**Table 3).** The feature extraction workflow yielded a producer's accuracy of 85% with a user's accuracy of 76%. Here, the producer's accuracy represents the ratio of correctly identified buildings to all identified buildings in the ground truth dataset. Additionally, the user's accuracy represents the ratio of correctly identified buildings to all classes in the ground truth datasets (Janssen & Vanderwel, 1994). When tested, the validation yielded a kappa coefficient of 0.62. Here, the kappa coefficient was used because it accounts for the possibility that a classification could have occurred by random chance (Foody, 2002). The kappa measure of 0.62 indicates that there the buildings identified in the feature extraction workflow are substantially representative of what is actually present.

We then used the DRPS to correct inaccurately classified parcels from the LIDAR validation dataset to minimize the error in the final change analysis. The final

2009 baseline for change analysis consists of a combination of LIDAR classified parcels and some corrected DRPS parcels.

Table 3: Validation of LIDAR building detection using the 2009 Detroit Residential Parcel Survey (DRPS). Only parcels that were classified as "residential" were used for validation. This accounts for approximately 80% of the total parcels. The building detection workflow correctly identified 85% of the parcels (both as containing or not containing a structure).

LIDAR	DRPS Structure	DRPS Vacant
Structure	222176	23350
Vacant	27952	66505

2.5.2 Five-year Change in Detroit

Using the classified 2009 and 2014 parcels in Detroit, a five-year change map was created with four categories: structure, vacant lot, new structure, and demolished structure. Here “structure” represents parcels that contained a structure in 2009 *and* 2014 while “vacant lot” represents parcels that did not contain a structure in 2009 *nor* 2014. The “new structure” category is reserved for the small number of parcels in which a structure was not present in 2009, but was present in 2014. Lastly, “demolished structure” represents parcels where a structure was present in 2009, but was removed by 2014. In this study, we define the word structure to mean residential or commercial buildings.

We examined 379,549 parcels in Detroit from 2009-2014 and found that 87.6% of the parcels did not change between the years. **Figure 5** shows the categorized change in each parcel for the entire city. We found 299,784 parcels that were classified as containing a structure in 2009. In 2014, 12.9% (37,453) of these parcels lost their structure. These demolished parcels accounted for 9.9% of the total number of parcels in the city. The decrease in the number of parcels containing a structure led to a 52.6% increase in the number of vacant lots. New builds were drastically overshadowed by the demolished structures, accounting for <1% of the total number of parcels in the city.

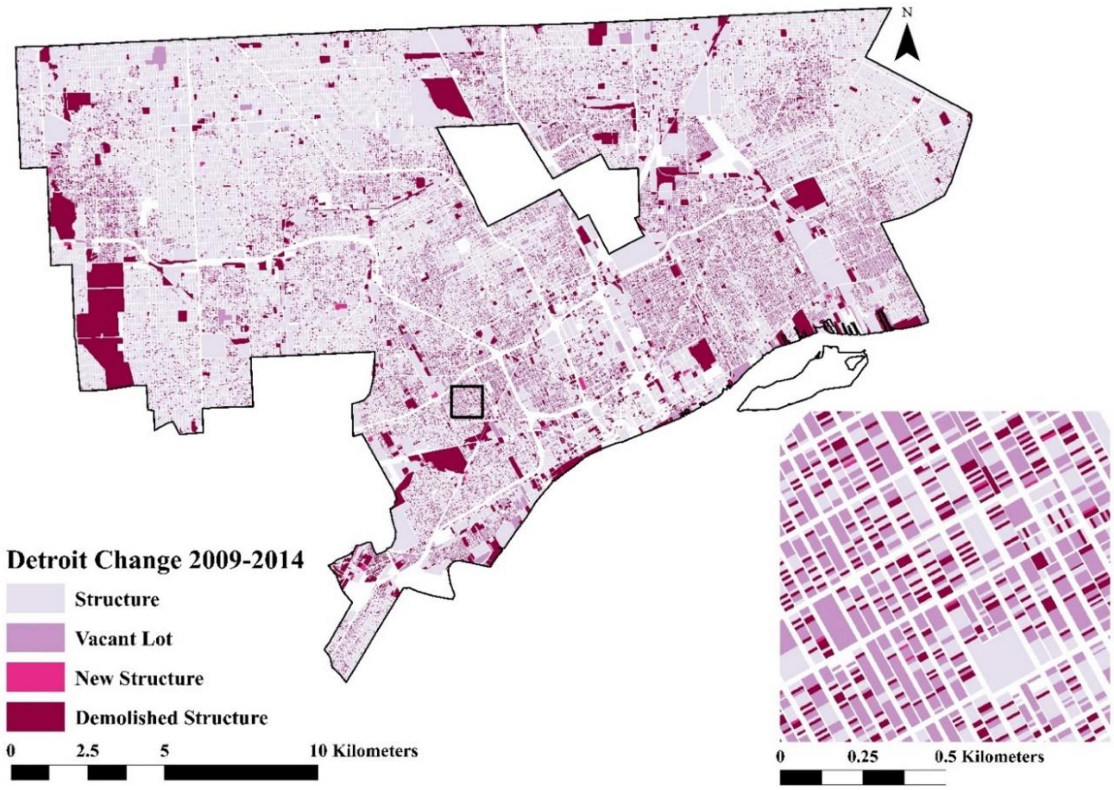

Figure 5: Five-year change map of Detroit using LIDAR and DRPS parcels from 2009 and the 2014 Motor City Mapping project. Inset shows a 1 km^2 sample area. Parcels classified as "Structure" contained a structure in both 2009 and 2014. Parcels identified as "Vacant Lot" were classified as being such in both 2009 and 2014. Parcels classified as "New Structure" or "Demolished Structure" saw the addition or removal of a structure from 2009-2014. As can be seen by the 1 km^2 sample area, vacant parcels

2.5.3 Change in Youngstown

2.5.3.1 Orthophotography Change

Of the 6,474 parcels that were manually classified for 1994, 2006 and 2013 we found that 5,149 (79.53%) remained unchanged (**Table 4a)** for all three years. From 1994 to 2006, we identified that 8% of the parcels had structures removed while 5% saw new builds (**Table 4b.**). The timeframe from 2006 to 2013 also saw an approximate 8% removal of structures and 15% of which were parcels where a new build occurred from 1994 to 2006. During this time only 2% of parcels saw new builds and of these 39% were on parcels that had previously had a structure demolished. The year-to-year changes are highlighted in **Figure 6** where 1 = structure present and 0 = no structure.

Table 4a: Changes in the number of parcels that contained a structure or did not contain a structure. Total Unchanged, Demolished, and New Build are based upon the previous time step.

1994		2006		2013			
Structure	**No Structure**	**Structure**	**No Structure**	**Structure**	**No Structure**	**Total**	**Total**
●		●		●		2221	34.3%
	●		●		●	2928	45.2%
	●	●		●		253	3.9%
	●		●	●		88	1.4%
	●	●			●	77	1.2%
●			●	●		56	0.9%
●			●		●	45	6.7%
●		●			●	416	6.4%

Table 4b: Changes in the number of parcels that contained a structure or did not contain a structure. Total Unchanged, Demolished, and New Build are based upon the

Year	Number of Parcels				
	Structure	**No Structure**	**Total Unchanged**	**Demolished**	**New Build**
1994	3128	3346	-	-	-
2006	3507	2967	5653	491	330
2013	3856	2618	5837	493	144

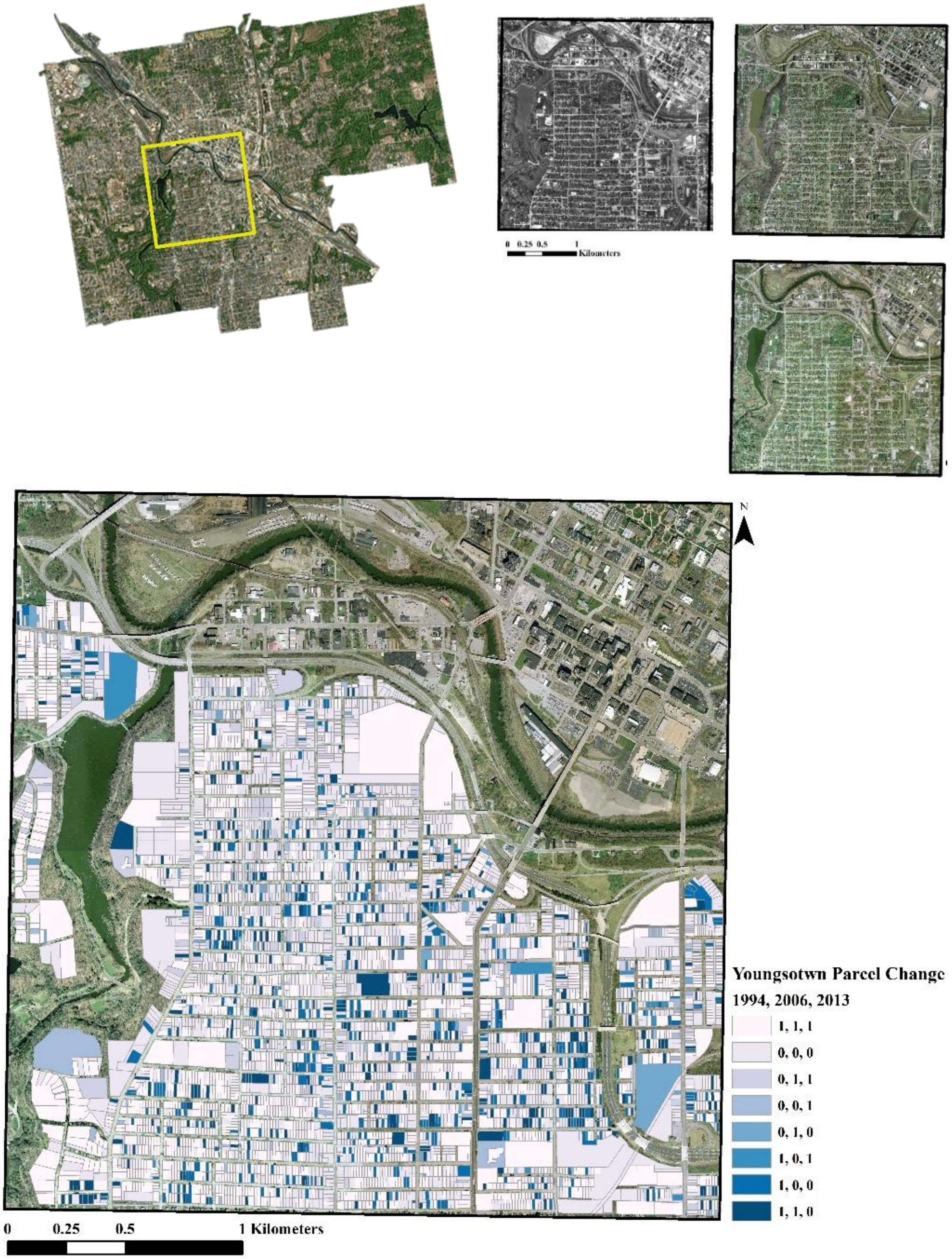

Figure 6: Top left: Box denotes 9 km^2 study region in south central Youngstown, Ohio used for study. Top right: Orthoimagery for 1994 and 2006. Right: Orthoimagery for 2013. Bottom: 6,474 manually classified parcels showcasing the change in structure presence from the aforementioned years where 1 = structure present and 0 = no structure.

2.5.3.2 Ten-year Demolition Change

Due to the labor intensive task of manually classifying parcels with aerial imagery, we chose to examine additional data sources. Here we demonstrate that demolition records can be applied to identify parcels that had a structure removed. This change can be viewed in **Figure 7** where a 1 km^2 sample region is presented to show the change in higher detail. The demolition records indicated that of the 61,387 total parcels in the city, 4,002 had structures removed during the decade from 2006-2016. This accounts for 6.52% of the total parcels. Although this data is useful for tracking demolished structures, it provides no insight into other parcel classifications such as continued structure presence. However, this type of data can be used to validate classified products. Here we use the demolition data to validate the orthoimagery classification for the 2006-2013 range. We removed demolition records prior to acquisition date of the 2006 imagery and after the acquisition date of the 2013 imagery. The validation yielded a user's accuracy of 71% and a producer's accuracy of 79%.

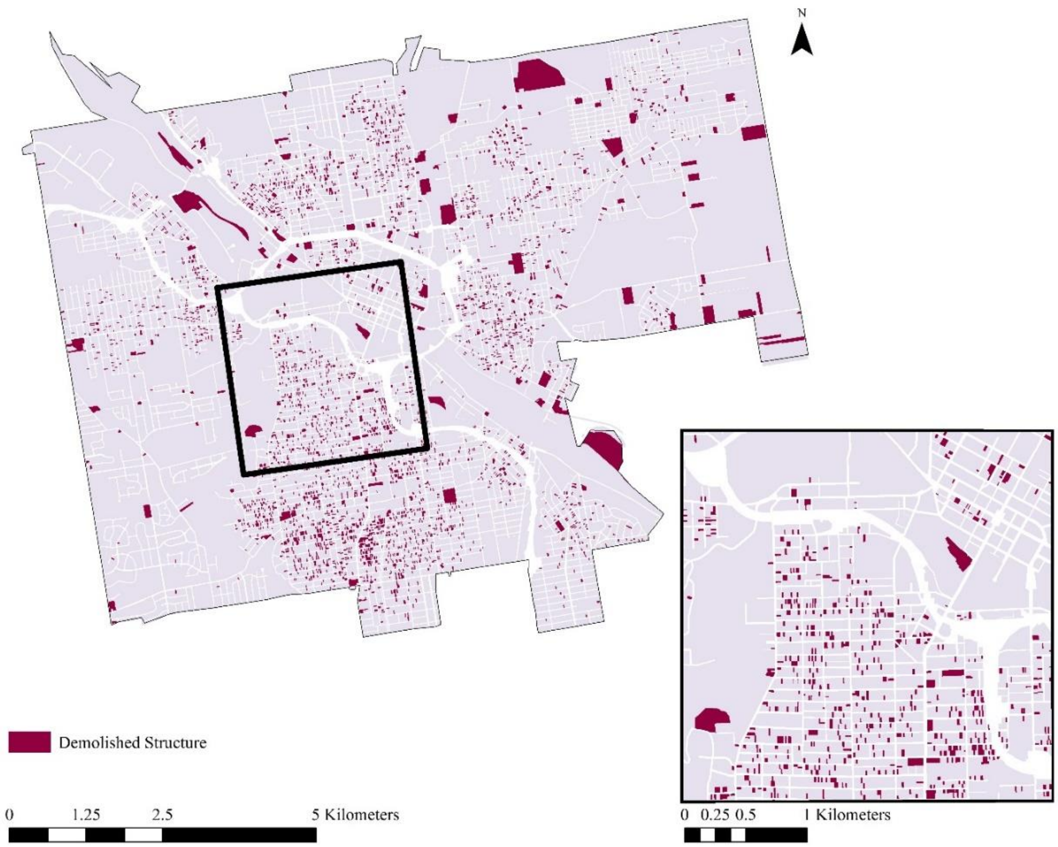

Figure 7: Ten-year change map of Youngstown using City of Youngstown demolition records. This change only highlights parcels that have had structures removed.

2.6. Discussion

We have found dearth in shrinkage literature which acknowledges the impact of drastic population declines on land cover in the United States. If studied using conventional approaches to urban land cover change such as the use of products with resolutions of 30 meters or coarser, small details on the surface are likely to be overlooked. High resolution and very high resolution satellite products are available, but often at a high cost due to the vast size of many of these shrinking cities. The use of publically accessible data at no-cost, such as LiDAR, GIS datasets and aerial orthophotos, are the most cost efficient means of performing a simple land cover change analysis for an extended period of time.

LiDAR is accessible via the USGS and can be used to extract features and create digital elevation and surface models at very high resolutions. The manner in which LIDAR point clouds are classified has changed throughout the years, causing inconsistencies in the representation and user-friendliness of the data. Additionally, low point density occasionally makes it difficult to identify specific features. In this study, LIDAR data for 2006 is available in Youngstown, however the feature extraction method we applied in Detroit was unable to accurately identify structures in Youngstown due to the lower point density (~2 points/10m^2). Perhaps the most significant challenge when using LiDAR data in land cover change studies is the lack multiple years from which to draw data. In this study, we were only able to use LIDAR from 2009 in Detroit. Like many land cover studies that use LiDAR, ancillary data was also needed (McCarley et al.; Radoux & Defourny; Singh et al., 2012; Sturari et al., 2017; Wu et al., 2016; Zhou et al., 2009). The use of LIDAR in combination with survey data from the MCM allowed us to generate a city-wide map showcasing the changes occurring on the urban landscape in Detroit. While this study allowed us to capture a snapshot of the arguable reversal of urbanization in the heart of the United States, the addition of multiple LIDAR years would have been beneficial.

Ancillary data in Detroit is far more available than for other shrinking cities, thanks primarily to efforts of blight task force organizations committed to preserving history and ridding the city of decay. Unlike Detroit, Youngstown does not possess a city-wide survey dataset that contains detailed information about each property, but we found that the use of freely available orthoimagery and GIS datasets were useful when looking for alternative data sources. In this study we used a combination of orthoimagery and demolition records to examine the shifting landscape in Youngstown. Orthoimagery is advantageous in that it is captured at a high spatial resolution and is often available for periods of time stretching multiple decades. In examining a shrinking city, using historic orthoimagery to monitor urban land cover change could provide more insight into the relationship between human environmental interactions (Geri, Amici, & Rocchini, 2010). However, using orthoimagery can be challenging and labor intensive because land cover types are not distinctly differentiated. Additionally, using older and coarser imagery makes features difficult to visualize and this could increase error rates. Manual classification is entirely based on human interpretation and without ancillary data to validate against, it is difficult to tell if the land cover is being accurately represented.

Youngstown consistently updates their public GIS databases, such as demolition records, allowing researchers and the municipality to monitor the landscape changes frequently. In Detroit, the last major update of in-situ data was carried out in 2013. While this short change in time may seem trivial, we have demonstrated that Detroit saw the removal of structures on approximately 7,500 parcels per year, suggesting that there is a need for frequent updates to geospatial databases.

2.7. Conclusion

The urban landscape in the United States is constantly changing, but not always in the typically researched context of urbanization and growth of built environment. Many cities in the Midwestern region of the country, such as Detroit and Youngstown, have been experiencing drastic population losses for over a half-century. While these areas have been thoroughly studied in terms of socio-economic implications of population loss, few studies to date have explored how the shifting dynamics are impacting the built environment in these shrinking. This study maps at the parcel scale how the presence of residential and commercial structures has changed in Detroit and Youngstown throughout various time periods. The use of LiDAR data in conjunction with the MCM survey data to classify parcels in Detroit allowed this study to map a five-year change for the entire city at a higher resolution than other publicly accessible data products. In Youngstown, the use of orthoimagery in conjunction with GIS data showed respective nineteen-year and ten-year changes in the presence of structures.

The minimal overall availability of current and publicly accessible data could inhibit financially limited municipalities from conducting these types of studies. There is a strong need within the scientific community to increase availability of high quality datasets. Programs such as the USGS' 3DEP initiative are productive in increasing the coverage of data available, but there is still a problem with limited timeframes. It is understood that historically, the cost of collecting airborne LiDAR data has been high, but technological advances have begun to lower those costs (Chen, 2007). This study has shown that the rate of loss of structures in these cities is significantly higher than the rate of structure replacement. The fast removal of the built environments could potentially have environmental implications in shrinking cities, suggesting a need for the continued monitoring of the shrinking urban landscape in these regions (D. Haase, 2013; Schetke & Haase, 2008).

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